Vicinity-based DTN Characterization

Tiphaine Phe-Neau, Marcelo Dias de Amorim, Vania Conan

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Tiphaine Phe-Neau*
UPMC Sorbonne Universites
tiphaine.phe-neau@lip6.fr

Marcelo Dias de Amorim*
CNRS and UPMC Sorbonne Universites
marcelo.amorim@lip6.fr

Vania Conan
Thales Communications
vania.conan@fr.thalesgroup.com

ABSTRACT

We relax the traditional definition of contact and intercontact times by bringing the notion of *vicinity* into the game. We propose to analyze disruption-tolerant networks (DTN) under the assumption that nodes are in κ*-contact* when they remain within a few hops from each other and in κ*-intercontact* otherwise (where κ is the maximum number of hops characterizing the vicinity). We make interesting observations when analyzing several real-world and synthetic mobility traces. We detect a number of unexpected behaviors when analyzing κ-contact distributions; in particular, we observe that in some datasets the average κ-contact time decreases as we increase κ. In fact, we observe that many nodes spend a non-negligible amount of time in each other's vicinity without coming into direct contact. We also show that a small κ (typically between 3 and 4) is sufficient to capture most communication opportunities.

1. INTRODUCTION

"How much time do two nodes spend within communication range of one another and how long does it take for them to meet again after having left each other?" These questions are central to most works on disruption-tolerant networking (DTN) and concern the problem of evaluating the *contact* and *intercontact* times among nodes [2, 7, 12]. Such analyses have fundamental practical impact, as they serve as a substrate for the design of forwarding strategies that better schedule transmissions based on the history of mobility. Noticeable examples are Prophet [9], Spray and Wait [15], and SSAR [8].

In this paper, we propose a different evaluation of the dynamics of disruption-tolerant networks by integrating the notion of node *vicinity* in the equation. Instead of considering only direct communications among nodes, we suggest extending the notion of "contact" to the zone within a few hops. The impetus for this proposal comes from the observation that a significant fraction of the pairs of nodes remains nearby (within a few hops) when not in direct contact. To this end, we use the κ*-vicinity*[1] as the basis of our analyses, where κ stands for the maximum number of hops separating two nodes. We define and analyze two temporal measures that are the κ*-contact* and the κ*-intercontact* times. We analyze their aggregated distributions and keep pairwise analyses for further study.

The interests of relying on an extended view of contacts and intercontacts are manifold. First, one obtains a finer characterization of the network, as we observe in real-world mobility traces that many pairs of nodes are frequently nearby without any direct contact. Second, it becomes easier to tune forwarding protocols as by introducing very little overhead (to discover the neighborhood) a node can discover significant proximity with other nodes. Third, by using short multihop opportunities, end-to-end delays can be decreased.

We analyze the time distributions for the κ-contact and the κ-intercontact times using both real-world and synthetic mobility traces and make a number of interesting observations. In a nutshell, we reveal the following findings:

- *Different classes of datasets.* We observe from our analyses that there are basically two different types of behaviors. When extending the contact notion to a node's vicinity, one would expect κ-contacts duration to increase. However, in some datasets, increasing κ leads to a higher probability of having shorter contacts, which is a quite unexpected result. We refer to these patterns respectively as *dense* and *light* distributions.

- *Existing analyses hold for κ-vicinity.* We confirm that the main observations found in the literature still apply in the context of our study. This means that the main principles of opportunistic communications remain the same. This is a good point as existing opportunistic protocols can directly benefit from our findings.

- *Close vicinity is enough.* We observe for the datasets we analyze that it is enough to extend the vicin-

*Authors carried out part of the work at LINCS (`www.lincs.fr`).

[1] Also referred to as the κ-neighborhood.

ity to a few hops (typically three or four) to capture most of the local communication opportunities. Such a threshold enables low costs for vicinity composition gathering. This also holds for networks with a large diameter.

After introducing and formalizing our proposal, we develop an extended analysis of well-known real-world and synthetic mobility traces. We then discuss the several time distributions and observations we make. Although out of the scope of this paper, we also provide some insights into the applicability of the proposed work in the design of more efficient DTNs.

2. BACKGROUND

2.1 Related Work

The most intuitive characterization of DTNs relies on the distribution of contact times. A contact occurs when two nodes are within each other's wireless communication range and can perform transmission. We consider networks with bidirectional links. In an early work, Vahdat and Becker investigated the impact of wireless ranges on message delivery [17]. Hui et al. analyzed contacts to derive affinities between individuals and likeliness of meeting [6]. Chaintreau et al. were pioneers in determining the possibilities of efficient transmission in networks through the history of contacts [3]. Contact is not the only meaningful parameter. To make the most of opportunistic communications, understanding intercontact times is also important.

Intercontact distributions indicate when nodes will next be able to transmit data to other devices. In the literature, we observe two main definitions for intercontact. The inter-any-contact notion, meaning the time interval elapsed between two subsequent contacts independently of the identities of the neighbors. The second definition, the pairwise intercontact time, involves a specific pair of nodes. It relates to the time two nodes wait before meeting again after moving away from each other. Leguay et al. thoroughly studied pairwise intercontact distributions in well known experimental datasets. They found these distributions well fitting either log-normal laws or exponential distributions [4]. Chaintreau et al. argued that pairwise intercontact times follow power law distributions over a specific time range [2]. In a similar study, Karagiannis et al. found that pairwise intercontacts fit diptych distributions – power law followed by exponential decay [7]. Recently, Passarella and Conti examined aggregate intercontact times and found them not to be the exact mirror of pairwise intercontact times [12].

2.2 Positioning

Although our work is inline with the contributions found in the literature, we propose to characterize DTNs using a different point of view. Previous analyses use one-to-one or one-to-all approaches for characterization. We argue in favor of an in-between approach to leverage a group-to-all vision. In this work, we take into account the immediate vicinity beyond simple contact for every node. We consider a subset of every node's connected component and study the effects of our group-to-all vision on DTN characterization. Using the κ-vicinity knowledge, we extend previous analyses to observe the impact of such point of view on DTN understanding.

To study the behavior of contacts within a node's κ-vicinity, we did not extend a node's wireless range to influence contact possibilities as Vahdat and Becker did. For intercontact patterns, as previously pleaded by Leguay et al., we base our analysis on the pairwise intercontact definition. We rely on our earlier findings that many pairs of nodes, when not in direct contact, remain nearby (within very few hops) [13]. The extension of contact and intercontact to a vicinity notion brings logical variation in previous intercontact and contact analyses. We perform state-of-the-art examination on our extended notions to understand how different our results are when compared to previous pairwise analyses [2, 7].

3. FROM THE VIEWPOINT OF VICINITY

Our modern society is tied by the relationships people share with one another. Social network studies showed how people interact based on social ties and how this can be used in networking when they form groups at given times [1, 10]. However, existing DTN protocols still maintain a contact-only vision for their decisions; in other words, they overlook the perspective of nearby nodes. Given people's tendency to colocate in specific places at explicit times, why should we underestimate such information?

3.1 The κ-vicinity

We want to embody the vision a mobile node has of its neighborhood. To this end, we consider the κ-vicinity of a node instead of only the direct neighbors:

DEFINITION 1. ***κ-vicinity.*** *The κ-vicinity $\mathcal{V}_\kappa^i$ of node i is the set of all nodes within κ hops from i.*

We use the term κ-vicinity to avoid any confusion with the tradition "n-hop-neighborhood" terminology. We assume that the n-hop-neighborhood indicates the nodes *exactly* at n-hops, while κ-vicinity gathers all the nodes *up to* κ hops. In Figure 1, we illustrate the 2-vicinity of node i.

The κ-vicinity brings the immediate surrounding knowledge. This is an interesting point of view for opportunistic networks because it extends a node's knowledge to immediately useable communication opportu-

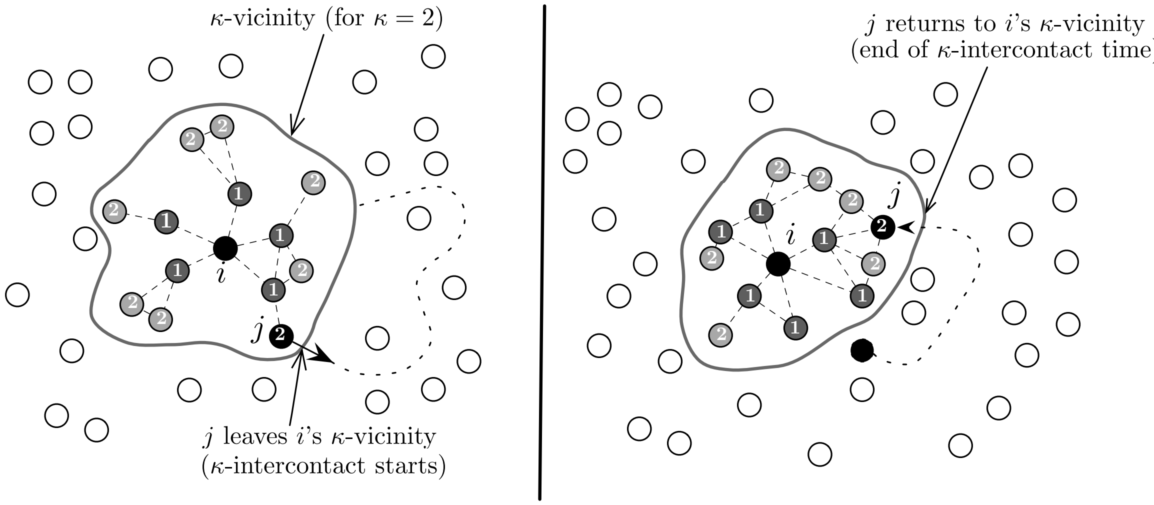

Figure 1: Node i's κ-vicinity and the κ-intercontact phenomenon. For the sake of clarity, we only display connectivity links and shortest hop distance from i within the κ-vicinity.

nities. The κ-vicinity empowers a node's reach in the network [14].

3.2 κ-contact and κ-intercontact

We are now ready to make the necessary definitions for the rest of our work.

DEFINITION 2. ***κ-contact.*** *Two nodes are in κ-contact when they dwell within each other's κ-vicinity, with $\kappa \in \mathbb{N}^*$. More formally, two nodes i and j are in κ-contact when $\{i \in \mathcal{V}_\kappa^j\} = \{j \in \mathcal{V}_\kappa^i\}$. In other words, a contemporaneous path of length at most κ links i and j.*

We also need to grasp the intercontact observations for our vicinity viewpoint. The literature definition of mere intercontact is when two nodes are not in contact. Therefore, we consider κ-intercontact when two nodes are not in κ-contact. These are complementary notions. Another way to see it is as follows: if node i maintains knowledge about its κ-vicinity, it is in κ-intercontact with any node beyond its κ-vicinity. In Figure 1, node j leaves i's κ-vicinity and then gets back some time later, characterizing a κ-intercontact interval.

DEFINITION 3. ***κ-intercontact.*** *Two nodes are in κ-intercontact while they do not belong to each other's κ-vicinity. Formally speaking, two nodes i and j are in κ-intercontact when $\{i \notin \mathcal{V}_\kappa^j\}$ or $\{j \notin \mathcal{V}_\kappa^i\}$. There is no path of length κ or less linking i and j.*

Note that 1-contact matches the contact notion and 1-intercontact corresponds to usual binary intercontact.

4. DATASETS

To perform our analysis, we selected real-life datasets and synthetic models displaying specific scenarios. Each of them embeds characteristics of real-life patterns that DTN wants to leverage. Real-life measurements used devices capturing other devices presence within a 10m wireless range.

Infocom05 measurement was held during a 5 day conference in 2005 [2]. 41 attendees carried iMotes collecting information about other iMotes nearby. We study a 12-hour interval bearing the highest networking activity. Each iMote probes its environment every 120 seconds. *Infocom05* represents a professional meeting framework.

Rollernet had 62 participants measuring their mutual connectivity with iMotes while they where riding a dominical rollerblading tour during 3 hours in Paris [16]. Researchers set devices to send beacons every 30 seconds. These measurements show a specific sport gathering scenario.

Unimi is a dataset captured by students, faculty members, and staff from the University of Milano in 2008 [5]. They involved 48 persons with special devices probing their neighborhood every second. *Unimi* provides a scholar and working environment scenario.

RT is a mobility model correcting flaws from the Random Waypoint model [11]. We sampled the behavior of 20 nodes following this model on a surface of 50 x 60 m^2 with speed between 0 and 7 m/s and a 10m wireless range for vicinity sensing.

Community is a social-based mobility model [10]. It tends to colocate socially-related nodes in specific locations at the same time like groups of friends would do. We simulated 50 nodes with a 10m wireless range on a 1,500 x 2,500 m^2 plane during 9 hours.

5. INTERCONTACT DISTRIBUTIONS

Intercontact patterns in DTN sprang many inspiring analyses as seen in Section 3. Studying intercontact duration distributions helps researchers quantify how long a node will have to wait before its next encounter. Figure 2 represents aggregated complementary cumulative density function (CCDF) of binary (traditional) intercontact and respective κ-intercontact durations for every pair of nodes. These CCDFs indicate the probability of a κ-intercontact lasting longer than t seconds.

5.1 Binary intercontact

As Karagiannis et al. observed, we also find that all binary intercontact CCDFs follow a straight line up to a knee point when both x-axis and y-axis are on logarithmic scale. This implies power laws for each binary intercontact distributions until the observed knee point also known as the characteristic time. In *Unimi*, we observe a knee point for binary intercontact at around 50,000 seconds. After plotting distributions with a linear scale on the x-axis and maintaining the log scale on the y-axis, we also observe that distributions can be approximated by a straight line beyond the knee point. In Figure 2, the phenomenon is clear for *Unimi*. This hints exponential decays for distribution tails. Observations on binary intercontact match results of previous studies.

5.2 κ-intercontact

As of κ-intercontact distributions, we find their general overlook to be quite similar to their respective binary intercontact distributions except for *Community*. κ-intercontacts display partial displacement after some point with a sharper slope for each curve. The larger the κ parameter, the more important the bottom left shift for each distribution. The concept of κ-neighborhood logically reduces κ-intercontact times. The wider a node's vicinity knowledge, the later this latter detects a node's departure from its vicinity and the quicker it detects its comeback resulting in shorter κ-intercontact durations. We see that for $\kappa \geq 6$, CCDFs aggregate.

An interesting remark is how κ-intercontact distributions exhibit the same properties as binary intercontacts. They follow power laws until a specific point (the characteristic time) and then carry exponential decay. In Figure 2, beyond 50,000 seconds, *Unimi*'s 2-intercontact curve is a vertical shift of the binary intercontact CCDF. The same occurs for further κ-intercontacts. However, an important information is that the knee point found for binary intercontact corresponds to changing points for κ-intercontact distributions. In *Unimi*, κ-intercontact curves ($\kappa \geq 2$) quickly decrease after the characteristic time found at 50,000 seconds.

Table 1 displays average intercontact duration and Table 2 the number of intercontacts intervals for each dataset. Except for *Community*, the higher κ gets, the lower the average κ-intercontact length. This enforces our rational expectations of κ-vicinity reducing κ-intercontact duration with higher κ. We remarked decreasing cumulated κ-intercontact times for each κ. We also observe a logarithmic growth in the number of κ-intercontact intervals.

5.3 Observations

The *Community* dataset stands out because of its non-monotonic average κ-intercontact duration and evolution of the number of intervals. When the average length grows, the number of κ-intercontact intervals decreases. This still results in a decreasing cumulated κ-intercontact duration for each κ. It enforces our first thoughts in the benefits of κ-vicinity for κ-intercontact times.

Under the assumption that nodes in the vicinity dwell within low delay reach, κ-intercontact duration decreases with larger κ, strengthening our belief that κ-neighborhood is beneficial to DTN protocols. The fact that characteristic time in all intercontact distributions corresponds is also an important finding. It could help protocols like Prophet, Spray-and-Wait, or SSAR maintain their actual intercontact-based approach and extend them to their vicinity to benefit from shorter κ-intercontact times.

6. CONTACT AND κ-CONTACT ANALYSES

Contact is the main feature for opportunistic mobile networks. Analyzing its distribution gives us insights into how protocols can benefit from these contact opportunities, as κ-contacts happen to be an extension of the strict contact definition. Instead of considering contact between neighbors at a 1-hop distance only, we analyzed the potential of transmission to nearby nodes within the κ-vicinity. These paths enable low delay transmissions and a better neighborhood reach for a network node.

6.1 κ-contact duration distributions

In Figure 3, we display aggregated CCDFs of contact alongside κ-contact duration for every pair of nodes in each experiment. These CCDFs indicate the probability of a κ-contact lasting longer than t seconds.

For *Infocom05* and *Rollernet*, their CCDFs maintain comparable aspects. We observe a small upper right shift for larger values of κ. As the κ-contact notion increases the node's vicinity scope, any nearby node may stay within the considered node's coverage longer than with a shorter sight vision. The higher the κ, the higher the probability of having longer κ-contact intervals duration. Above scanning granularity, lower κ results in curves with a sharper slope than curves of longer κ-contacts.

Like *Infocom05* and *Rollernet*, for $\kappa \geq 3$, *Commu-*

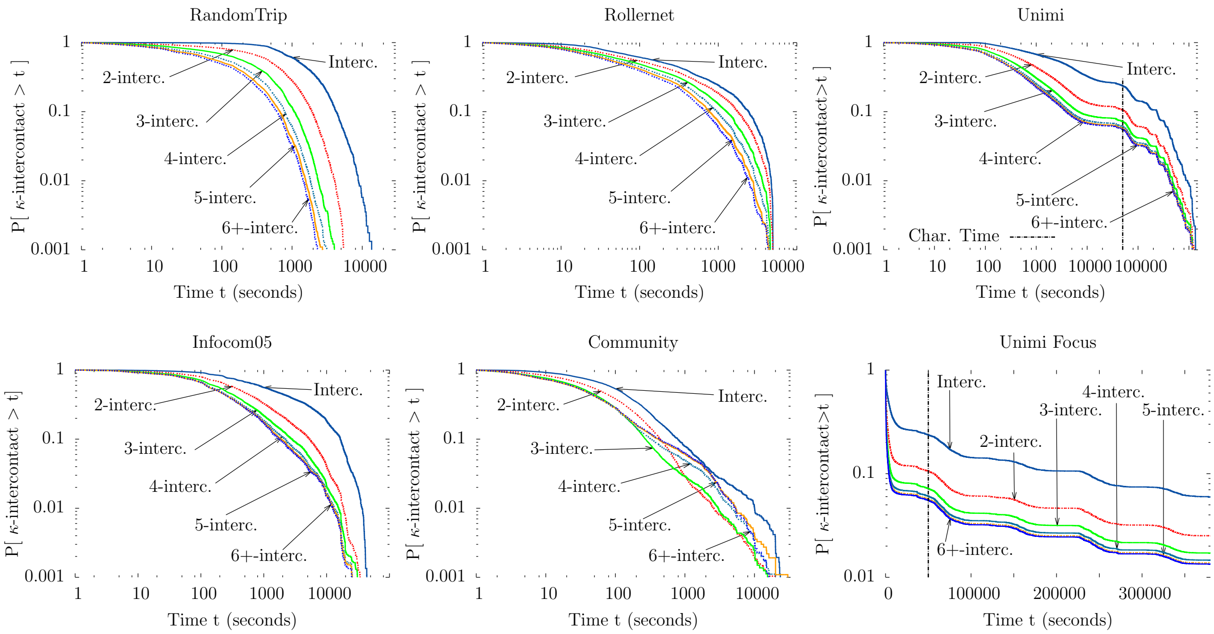

Figure 2: κ-intercontact distributions. Apart from Community, nodes display a lower probability of obtaining κ-intercontact intervals lasting longer than t seconds for high κ. On average, κ-vicinity reduces κ-intercontact times. Distributions follow power laws up to a characteristic time and display exponential decay afterwards. All κ-intercontact distributions knee point concord. Community has inconsistent κ-vicinity patterns for $\kappa \geq 3$. Interc. stands for Binary intercontact (logscale on both axes except Unimi Focus which is linear-log).

Table 1: κ-intercontact average duration in seconds.

Dataset	κ					
	1	2	3	4	5	6+
RT	1,874.3	772.2	415.7	291.5	238.4	213.1
Rollernet	738.3	555.3	412.2	328.2	273.6	242.5
Unimi	66,434.8	28,687.6	19,529.0	16,585.3	15,534.9	15,110.3
Infocom05	4,930.9	1,752.0	1,111.5	916.8	850.3	823.5
Community	525.3	232.4	193.5	262.2	317.1	295.9

nity's κ-contact CCDFs bear the same overall outlook with a sharper slope for smaller κ. For 1- and 2-contact CCDFs, we hint an interesting phenomenon. We find two junctions around 400 seconds and another at 1,050 seconds. Opposed to our previous expectations, we have a better chance of getting contact of duration $D \in [400; 1,050]$ seconds than 2-contact slots of the same duration.

For *RT* and *Unimi*, their 1-contacts bear different behaviors than κ-contacts when $\kappa \geq 2$. As hinted in the *Community* dataset, for some times κ, the probability of obtaining contacts slots lasting longer than t seconds is higher than the probability for the same t in other datasets. In Figure 3, this phenomenon clearly appears for *Unimi*. In *RT*, $t = [0; 500] \cup [1,050; 10,000]$ seconds. In *Unimi*, the assertion is valid for the whole distribution. For $\kappa \geq 3$, CCDFs aggregate into an unique one. 2-contact distribution is a mixed behavior between 1-contact and larger values of κ.

6.2 Density related behavior

Due to the social nature of *Community*'s functioning, specific nodes tend to remain together and bring a high density around popular nodes. *Rollernet* is a dense sport setting and *Infocom05* has selective meeting points in the conference. They all exhibit an important node-centered density, whereas *Unimi* and *RT* bear light density around each nodes. The local density parameter may explain the difference between the κ-contact behaviors.

Figure 4 illustrates a situation detailing the unexpected behavior of κ-contact distributions in light settings. Lighter densities limits geographical κ-vicinity coverage and induces smaller κ-contact intervals. Dense

Table 2: κ-intercontact number of intervals.

Dataset	κ					
	1	2	3	4	5	6+
RT	2,264	5,041	8,258	10,516	11,862	12,629
Rollernet	2,529	7,460	12,357	15,789	17,622	18,422
Unimi	21,737	57,085	86,009	102,495	109,406	112,323
Infocom05	3,727	11,028	15,338	16,774	17,186	17,117
Community	3613	11,561	8,034	4,505	3,660	3,477

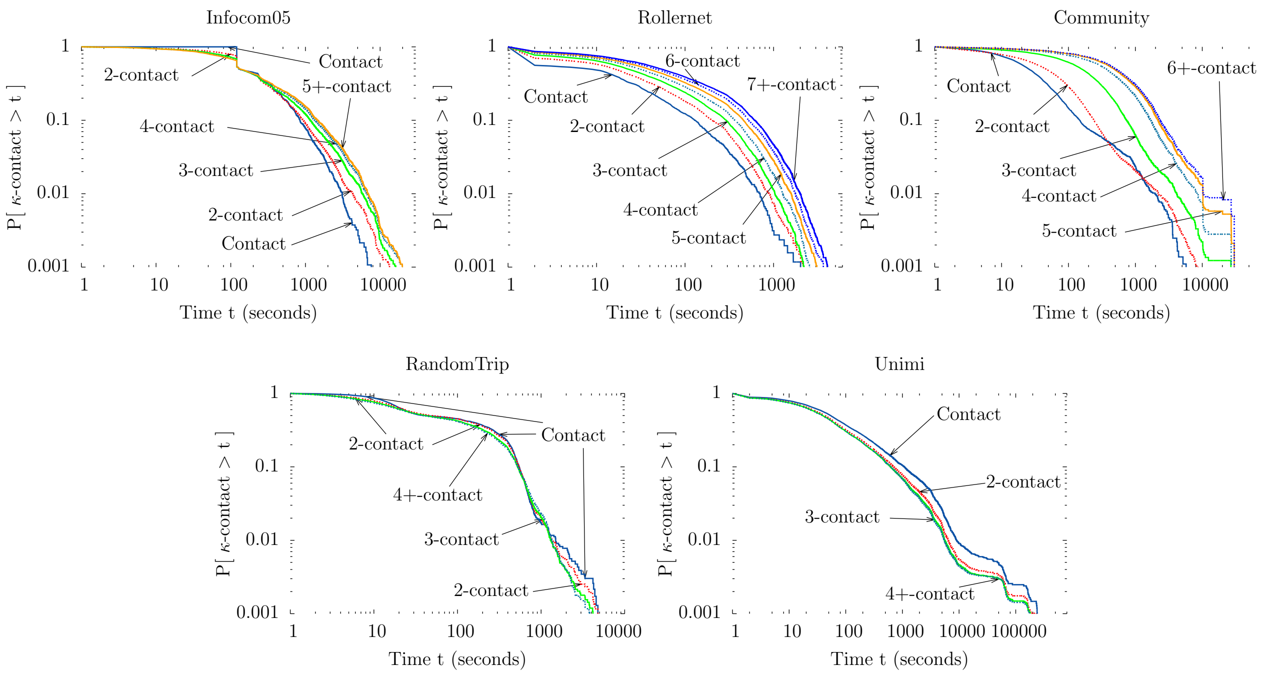

Figure 3: κ-contact distributions. There are two major patterns: (i) *dense distributions* where CCDFs having larger κ suffer a top right shift and a smoother slope than smaller κ, and (ii) *light distributions*, where all κ-contact distributions for $\kappa \geq 4$ aggregate and present a slight bottom left shift compared to the contact distribution (logscale on both axes).

settings ignite distributions like *Infocom05*, *Rollernet*, and *Community* and will be henceforth mentioned as *dense distributions*. Low density settings like *RT* and *Unimi* enable the second type of distributions mentioned as *light distributions*.

6.3 Average duration and number of intervals

In Table 3, we displayed the average duration of κ-contact intervals and in Table 4 the number of κ-contact slots for each of our five experiments. Two main behaviors arise. On the one hand, for *Infocom05*, *Rollernet*, and *Community*, we find an impressive continuous growth of average slots duration for every κ. On the other hand, *RT* and *Unimi* show the opposite evolution concerning average κ-contact duration. An increase in κ brings increased average κ-contact lengths.

For most datasets, we also find a logarithmic growth of the number of κ-contact intervals. Consequently, the number of intervals balances their length shortening. This testifies the growth in cumulated κ-contact durations in all datasets. Despite results observed in the previous section for *RT* and *Unimi*, for all our datasets, we find that larger values of κ increase the overall κ-contact duration and modify its distribution. The main difference lies in the fact that *Infocom05*, *Rollernet*, and *Community* experience longer κ-contacts for large κ than *RT* and *Unimi*, which have more shorter κ-contacts. In any case, both types have longer cumulated κ-contact times and it grows with κ.

6.4 Observations

We have seen how κ-contact distributions predominantly exhibit two behaviors: light or dense distributions. Dense distributions follow our logical expectations. These distributions have sharper slope for lower κ and therefore a stronger demarcation among them than

Table 3: **κ-contact average duration in seconds.**

Dataset	κ 1	2	3	4	5	6	7+
Infocom05	371.1	406.4	492.8	561.2	597.5	630.5	653.0
Rollernet	47.2	73.5	97.7	125.7	156.0	184.3	211.6
Community	96.3	138.7	358.6	751.9	1,000.9	1,123.21	1,135.5
RT	201.8	200.2	184.7	182.2	182.1	182.1	182.4
Unimi	1,324.6	901.2	820.7	796.7	791.5	801.5	798.2

Table 4: κ-contact number of intervals.

Dataset	κ 1	2	3	4	5	6	7+
Infocom05	3,735	11,071	15,412	16,870	17,288	17,221	17,117
Rollernet	5,106	15,410	25,200	32,630	36,286	38,110	38,586
Community	3,629	11,612	8,127	4,627	3,798	3,627	3,598
RT	2,316	5,146	8,385	10,645	11,992	12,759	13,128
Unimi	10,875	28,550	43,019	51,271	54,733	56,193	56,782

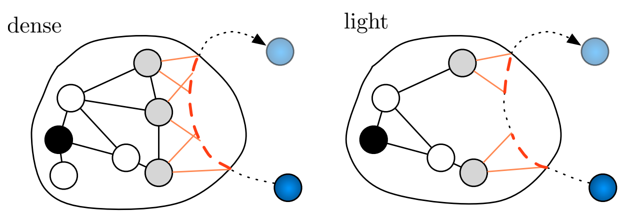

Figure 4: Density related behavior for κ-contact. Density modifies the coverage zone of a node's κ-vicinity. For dense settings, we have a long continuous κ-contact interval. For light situations, we obtain two smaller κ-contacts for the same walk.

the next variety. Light distributions show κ-contact distributions with comparable behaviors and no major demarcations. They quickly aggregate into a unique distribution above $\kappa \geq 4$. For these distributions, contrary to our primary beliefs, the probability of getting κ-contacts longer than t seconds is higher for shorter values of κ and contact durations.

However, for all measurements, the number of κ-contact intervals increases with every κ and springs a longer cumulated κ-contact time. Dense distribution obtains more large κ-contact intervals whereas light distribution has more short κ-contact intervals. Knowing which distribution fits, either light or dense, to a given situation modifies the way a protocol should consider its κ-vicinity. Adapting a routing technique to dense or light κ-contact distributions accordingly may help nodes leverage their κ-vicinity more efficiently than what is currently done.

7. κ-VICINITY ANALYSIS

Where most studies consider only the possibilities of contacts, using a node's vicinity sounds appealing to reduce κ-intercontacts and increase κ-contact times. With the κ-vicinity, we can measure the potential of such nearby companions in terms of opportunistic communications. Yet, we can wonder up to which point a node should survey its vicinity to leverage it.

7.1 Density

To mirror a node's specific κ-vicinity density, for each node, let $\mathcal{D}^i_\kappa$ be the density of nodes around i, obtained as

$$\mathcal{D}^i_\kappa = \frac{card(\mathcal{V}^i_\kappa)}{\tau}, \tag{1}$$

where $card(\mathcal{V}^i_\kappa)$ is the number of nodes in i's κ-vicinity and τ is the experiment duration. κ-density internal composition influences a node's κ-vicinity behavior. The more κ-contacts a node has, the more chances it has of getting $\{\kappa+1\}$-contacts. In Table 5, we present the average $\mathcal{D}^i_\kappa$. For datasets with participants moving slow and steady like *Infocom05*, *Unimi*, and *Community*, above a certain limit $\mathcal{D}^i_\kappa$ does not increase anymore and is limited by the network diameter. More dynamic or inconsistent patterns – *RT* and *Rollernet* – display logarithmic increase in $\mathcal{D}^i_\kappa$. For all cases, we verify $\mathcal{V}_\kappa$ growth with κ indicating the presence of nearby nodes useable as relays for κ-contact.

For any datasets, observing contacts only shows limited $\mathcal{D}^i_\kappa$. While observing the κ-vicinity up to a few hops – $\kappa = \{3, 4\}$ – increases $\mathcal{D}^i_\kappa$ by at least doubling it or even tripling it. For $\kappa > 4$, the increase rate is less striking or even null. Nevertheless, longer κ-contacts

Table 5: Average number of neighbors $\mathcal{D}^i_\kappa$ in a node's κ-vicinity (whole dataset duration).

	κ							
Dataset	1	2	**3**	**4**	5	6	7	8+
Community	2.0	4.1	4.6	4.9	4.9	4.9	4.9	4.9
RT	2.0	3.2	4.7	6.7	7.4	7.8	7.9	8.0
Infocom05	2.3	3.8	5.5	6.0	6.3	6.4	6.4	6.4
Rollernet	1.8	3.2	4.7	5.7	6.3	6.7	6.9	7.1
Unimi	0.15	0.25	0.31	0.35	0.37	0.38	0.38	0.38

in terms of path length may not be interesting because of potential path inconsistency due to all relays movements. Monitoring κ-vicinity up to a $\{3, 4\}$ threshold brings most of the local density a node can use.

7.2 Neighbors beyond contacts

An interesting situation occurs when pairs of nodes do not come into contact but belong to each other's κ-vicinity. Usual protocols miss this knowledge by overlooking the potential of nearby nodes. To analyze the impact of such situations, we studied the closest distance between nodes for all pair of nodes.

For *Unimi* and *Infocom05*, we find that respectively 92% and 91% of pair of nodes do come in contact. This can be explained by the datasets nature where people are coworkers and have to meet to exchange ideas. However, we find that even there, some nodes do not find themselves closer than a 2-hop distance respectively for 6% and 7% of them. Other datasets deprived of the specific aim of meeting each other like *Rollernet* and *Community* show that contact only represent 31% and 42% of the lowest distances. There, respectively more than 51% and 46% stay at the closest between 2 and 4-hop distances. In *RT*, all pair of nodes come into contact at one point or another. By observing the $\{3, 4\}$-vicinity, we manage to monitor additional situations of non-contact between nodes. As a result, we catch most pairwise κ-contacts occurring in a node's vicinity with only a threshold $\kappa = \{3, 4\}$.

8. IMPLICATIONS

Opportunistic Protocols. DTN protocols chose to leverage the obvious contacts – binary intercontact patterns. While they may appear sufficient to elaborate routing schemes, they ignore nearby communications possibilities. As DTN rely on human mobility patterns to generate encounters and topological proximity, we should make use of hot places in a map and hubs on the connectivity plane. Gathering a node's surrounding situation via the κ-vicinity knowledge can help us do so. We show that observing a node's κ-vicinity improves both contact opportunities and intercontact durations. Moreover, in Section 7, we explain how observing a node's κ-vicinity with $\kappa = \{3, 4\}$ is enough to be aware of most pairwise activity in the vicinity beyond contacts and to benefit from local densities.

Mobility Models. Musolesi et al. based their mobility model on social network theory [10]. Their model takes into account colocating patterns by mean of social attractiveness. Their intent, with HCMM proposed by Boldrini et al [1], is one of the most sensible we have seen in terms of binding synthetical models and social patterns. Still, they limit their approach to contact patterns which results in incoherent κ-contact and κ-intercontact distributions. In Figure 3, contact and 2-contact distributions intertwine whereas the κ-contact ($\kappa \geq 3$) do not and present the same demarcation as other *dense distributions*. In Figure 2, binary intercontact and 2-intercontact CCDFs present expected behaviors. We find 3+-intercontact behavior inconsistent. We warn users when using such mobility models, while issued traces respect essential social patterns, they may mislead users on other incidental parameters like κ-vicinity behaviors.

9. CONCLUSION

We propose a DTN characterization based on the vicinity viewpoint. Our motivation comes from the fact that most DTN protocols ignore their vicinity beyond one hop. We confirm previous results of Karagiannis et al. with regard to aggregated κ-intercontact behaviors, meaning that they follow power laws up to a given time and experience exponential decay afterwards. This allows current DTN protocols to leverage their κ-vicinity without too much change in their functioning. We also found that κ-contact distributions globally follow two patterns which are density related. Dense environments provide logical results of κ-contact duration extension with higher κ whereas light settings display inverted paradoxical patterns. Protocols should be aware of these patterns and treat them accordingly to benefit from this knowledge. Finally, we showed how limiting a node's awareness to their $\{3, 4\}$-vicinity is enough to benefit from most κ-vicinity advantages. As a next step, we plan on analyzing pairwise κ-vicinity behaviors on a strict pairwise level to enable better identification of peculiar events between nodes. We also would like to dive deeper into the κ-contact notion and understand the different path types resulting in κ-contact.

Acknowledgments

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